Detecting Fake News on Social Media: A Machine Learning Approach

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ABSTRACT

The rapid spread of fake news on social media platforms has significant consequences for society, influencing public opinion, election outcomes, and economic markets. This project develops machine learning models to classify news statements as real or fake using textual content. Here we will present the linguistic characteristics of news statements that have gone viral on social media by providing design tools to identify and contain the propagation of misinformation on the web. We used the PolitiFact dataset, simplifying its labels into binary classes, while we explore various machine learning algorithms along with feature extraction techniques to determine the most effective approach in detecting fake news.

KEYWORDS

Fake News Detection, Social Media Analysis, Machine Learning, Text Classification, Natural Language Processing

1 INTRODUCTION

The digital age has revolutionized how information is disseminated and consumed, with social media platforms playing a pivotal role in the rapid spread of news. However, this ease of information sharing has also led to the proliferation of fake news—false or misleading information presented as news—which poses real consequences for society. Fake news can influence how people think, sway election outcomes, and impact economic markets. For instance, fake stories about Hillary Clinton circulated extensively during the 2016 U.S. presidential election, potentially influencing voter opinions. Another example is a fake news report about an explosion injuring former President Barack Obama, which led to a loss of $130 billion in stock value.

Given the speed and low cost at which information spreads online, there is an urgent need for processes that can identify and alert users against fake news. This project aims to develop machine learning models to classify news statements as real or fake using textual content, thereby assisting in identifying and containing the spread of misinformation on the web.

2 RELATED WORK

The detection of fake news has become a critical area of research in natural language processing and machine learning. Previous studies have employed various techniques ranging from linguistic cue analysis to deep learning models. Wang [1] introduced the LIAR dataset, a benchmark dataset for fake news detection, which includes detailed labels and metadata. Other research has explored the use of ensemble methods and neural networks to improve classification accuracy [2, 3].

While significant progress has been made, challenges remain due to the complexity and subtlety of language used in fake news. Our work builds upon these foundations by utilizing the PolitiFact dataset and experimenting with multiple algorithms and feature representations to enhance detection performance.

3 DATASET

3.1 Source

The dataset used in this project is derived from PolitiFact, as described in the paper "Liar, Liar Pants on Fire: A New Benchmark Dataset for Fake News Detection" by Wang (2017) [1]. PolitiFact is a Pulitzer Prize-winning fact-checking organization that evaluates the truthfulness of statements made by politicians and public figures.

3.2 Exploratory Data Analysis

The dataset includes the following key attributes:

- **ID**: Unique identifier for each statement.
- **Label**: Original labels include 'true,' 'mostly-true,' 'half-true,' 'false,' 'barely-true,' and 'pants-fire.'
- **Statement**: The news statement to be classified.

3.3 Simplification of Labels

For the purpose of this project, the six original labels have been simplified into two classes to facilitate binary classification:

- **True Class**: Contains 'true,' 'mostly-true,' and 'half-true' statements.
- **False Class**: Contains 'false,' 'barely-true,' and 'pants-fire' statements.

3.4 Examples from the Dataset

3.4.1 *False News Statements.*

- "Says the Annies List political group supports third-trimester abortions on demand."
- "Health care reform legislation is likely to mandate free sex change surgeries."
- "Jim Dunnam has not lived in the district he represents for years now."

3.4.2 *True News Statements.*

- "When did the decline of coal start? It started when natural gas took off that started to begin in (President George W.) Bush's administration."
- "The economic turnaround started at the end of my term."

- "I'm the only person on this stage who has worked actively just last year passing, along with Russ Feingold, some of the toughest ethics reform since Watergate."

4 DATA PREPROCESSING

In the current digital landscape, the proliferation of misinformation presents significant challenges. Analyzing and classifying political statements for their truthfulness is essential for promoting informed discourse. This project focuses on preprocessing and analyzing a dataset of political statements to classify them as either 'true' or 'false'. The workflow includes systematic data cleaning, label transformation, text preprocessing, exploratory data analysis (EDA), word frequency analysis, and topic modeling using Latent Dirichlet Allocation (LDA). The goal is to uncover underlying patterns and themes within political discourse that can aid in the development of effective classification models.

To understand the structure, content, and initial issues of the dataset before proceeding with cleaning.

- Removed the 'id' column as it was not useful for analysis.
- Printed dataset information to check data types and identify missing values.
- Checked the number of rows with any null values.
- Recorded the length and shape of the data.

4.1 Data Cleaning

To remove any duplicate rows to prevent bias and maintain data integrity, we:

- Counted the number of rows before removing duplicates.
- Removed duplicate entries from the dataset.
- Counted the number of rows after removing duplicates.
- Calculated the number of duplicated rows that were removed.

To handle missing data by filling in missing values to maintain dataset completeness, we:

- Checked for missing values in each column.
- Replaced empty strings and NaN values with appropriate placeholders:
  - String columns: Replaced NaN with 'Unknown'.
  - Numerical columns: Replaced NaN with 0.
- Verified that there were no missing values left in the dataset.

4.2 Data Transformation

To simplify the classification task by mapping multiple labels into two categories using binary classification transformation: 'true' and 'false'.

- Mapped the original labels into 'true' if they were 'true', 'mostly-true', or 'half-true'; otherwise, mapped to 'false'.
- Displayed the distribution of the new binary labels.

The dataset now has 7,133 'true' statements and 5,657 'false' statements.

Table 1: Label Distribution

Label	Count
True	7,133
False	5,657

4.3 Text Preprocessing

To clean and standardize text data, making it suitable for analysis and modeling.

- **Lowercasing & Removing URLs:** Converted all text to lowercase to ensure uniformity and eliminated web addresses that do not contribute to content analysis.
- **Removing Emails, Numbers, Punctuation:** Removed email addresses to prevent personal data leakage, stripped out numerical data that may not be relevant, and cleared punctuation marks to simplify the text.
- **Removing Repeating Characters & Extra Whitespaces:** Reduced repeated characters to a single instance and cleaned up unnecessary spaces.
- **Tokenization:** Split text into individual words (tokens).
- **Removing Stopwords:** Removed common words that do not carry significant meaning (e.g., 'the', 'is').
- **Lemmatization:** Reduced words to their base form to treat different forms of a word as the same token.

Applied the preprocessing steps to each statement, creating a new `cleaned_statement` column. Displayed samples of the original and cleaned statements for verification.

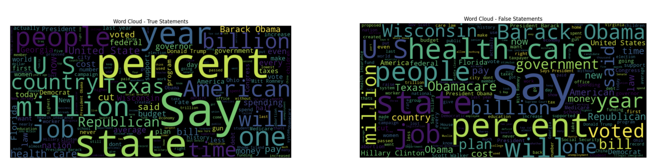
Table 2: Sampled Cleaned Data

Statement	Cleaned Statement
Says Donald Trump...	say donald trump...
No one claims...	one claim report...

4.4 Exploratory Data Analysis

To visualize the most frequent words in 'true' and 'false' statements, providing insights into the language used in each category.

We generated separate word clouds for 'true' and 'false' statements using the original (uncleaned) statements, creating visual representations where the size of each word indicates its frequency.



(a) True Statements (b) False Statements

Figure 1: Word Clouds with Original Statements

4.5 Word Frequency Analysis

To compare the frequency of words between ’true’ and ’false’ statements, identifying distinguishing words.

We created subsets of the dataset for ’true’ and ’false’ statements, vectorized the cleaned text to count word frequencies, identified the top 20 words in each category, and created a bar plot to compare word frequencies between ’true’ and ’false’ statements.

To identify the most common words across all statements in the dataset:

- Compiled all words from the `cleaned_statement` column.
- Calculated the frequency of each word.
- Listed the top 25 most frequent words.
- Visualized these words using a bar plot.

4.6 Topic Modeling with LDA

Preparing Data for LDA: To prepare the preprocessed text data for topic modeling using LDA, we tokenized the `cleaned_statement` column into lists of words, created a dictionary and corpus required for computing coherence scores using Gensim, and vectorized the cleaned statements for use with scikit-learn’s LDA implementation.

To evaluate the quality of topics generated by LDA models, we used a function to compute the coherence score.

Evaluating Coherence: To determine the optimal number of topics by evaluating coherence scores for different LDA models, we ran LDA models with the number of topics ranging from 1 to 10. For each model:

- Printed the top words for each topic.
- Calculated the coherence score.
- Recorded the coherence score for comparison.

To identify the number of topics that yields the highest coherence score, we determined that the optimal number of topics is 4, as it provided the highest coherence score.

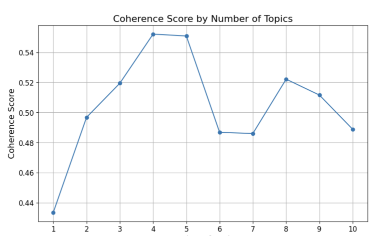


Figure 2: Coherence Score by Number of Topics

Training Final LDA Model: We trained the final LDA model with 4 topics, extracted the top words for each topic, manually assigned labels to each topic based on the top words.

To visualize the significant words in each topic, we generated word clouds for each of the 4 topics. The size of each word in the word cloud reflects its importance in the topic.

```
Training Final LDA Model.
Topic 1: city, texas, milion, people, year, say, rate, state, percent, job
Assign a label for Topic 1: Texas Economy and Employment Rates
Topic 2: law, insurance, said, clinton, bil, voted, republican, care, health, say
Assign a label for Topic 2: Health Care Legislation and Policy Debates
Topic 3: obamas, debt, united, year, percent, state, barack, say, president, obama
Assign a label for Topic 3: President Obama's Administration and National Debt
Topic 4: pay, milion, budget, bilion, cut, state, percent, say, year, tax
Assign a label for Topic 4: State Budget Cuts and Taxation Policies
```

Figure 3: Word Clouds for LDA Topics

5 FEATURE ENGINEERING

In our pursuit of building an effective fake news detection model, we recognized the critical role of feature engineering in transforming raw textual data into meaningful numerical representations that machine learning algorithms can interpret. We focused on three main aspects: analyzing feature variance, representing textual data through various vectorization techniques, and selecting the most informative features for our models.

5.1 Variance Analysis of Metadata Features

Understanding the variability within our dataset’s features is essential to ensure that our models can generalize well. We began by examining the variance of several metadata attributes in the dataset, specifically:

- **Subject**: The topic or category of the news statement.
- **Speaker**: The individual who made the statement.
- **Speaker Job**: The occupation or role of the speaker.
- **Speaker State**: The state associated with the speaker.
- **Speaker Affiliation**: The political affiliation of the speaker.

By converting categorical variables into numerical form using label encoding, we computed the variance for each feature. The variances were as follows:

Table 3: Variance of Metadata Features

Feature	Variance
Subject	1,721,274.76
Speaker	924,569.25
Speaker Job	106,300.04
Speaker State	749.53
Speaker Affiliation	40.06

The high variance in features like *Subject* and *Speaker* suggests a wide spread in their encoded numerical values, indicating a diverse set of topics and speakers in our dataset. Conversely, the relatively low variance in *Speaker Affiliation* reflects fewer unique political affiliations among the speakers.

5.2 Multicollinearity Assessment Using Variance Inflation Factor

Multicollinearity among predictor variables can adversely affect model performance by inflating the variance of coefficient estimates, making them unstable and sensitive to minor changes in the data. To detect multicollinearity, we calculated the Variance Inflation Factor (VIF) for each metadata feature in our dataset.

The results of the VIF analysis are presented in Table 4.

Table 4: Variance Inflation Factor (VIF) Values for Metadata Features

Feature	VIF
Subject	4.462
Speaker	3.813
Speaker State	5.291
Speaker Job	4.584
Speaker Affiliation	6.046

A VIF value greater than 3 is generally considered indicative of high multicollinearity. As shown in Table 4, all five categorical features—*Subject*, *Speaker*, *Speaker State*, *Speaker Job*, and *Speaker Affiliation*—exhibited VIFs significantly greater than 3. This substantial multicollinearity suggests that these features may provide overlapping information, potentially impacting model stability and interpretability negatively.

To address this issue, we conducted a Chi-Square test to select the top 100 features most significant in predicting the target variable. This feature selection process was applied to our textual data representations, specifically the Bag of Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF) models. Notably, none of the high VIF categorical features were among the top features selected by the Chi-Square test. This finding implies that these metadata features may not be as statistically significant in predicting the target variable compared to features derived from the textual data.

Based on these insights, we decided to exclude the high multicollinearity features from our final model. This decision aimed to:

- **Improve Model Stability**: By removing highly correlated features, we reduced redundancy in the data, leading to more stable and reliable coefficient estimates in the model.
- **Enhance Interpretability**: A streamlined model with fewer, more significant features is easier to interpret and understand, especially when the included features have a direct relationship with the target variable.
- **Focus on Statistically Significant Features**: Relying on the Chi-Square test results ensured that only the features with the strongest statistical relationship to the target variable were included.

In summary, our approach prioritized features based on their statistical significance and predictive power while consciously excluding those that could introduce multicollinearity. This strategy helps build a more robust model that generalizes better to unseen data and provides clearer insights into the factors influencing the target variable.

5.3 Textual Feature Representation

The core of our dataset comprises textual statements, which require transformation into numerical form. We explored three prominent techniques for text vectorization:

5.3.1 Bag of Words (BoW). The Bag of Words model represents text as a vector of word counts, disregarding grammar and word order but preserving frequency information.

- **Implementation**: We utilized *CountVectorizer* to convert the cleaned statements into a matrix of token counts.
- **Outcome**: The BoW representation resulted in a sparse matrix with a shape of (12,791, 12,197), indicating 12,197 unique tokens across all statements.

5.3.2 Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF builds upon the BoW model by weighting terms based on their importance, reducing the impact of commonly used words.

- **Implementation**: We applied *TfidfVectorizer* to compute the TF-IDF scores for each word in the corpus.
- **Outcome**: Similar to BoW, the TF-IDF representation produced a matrix of shape (12,791, 12,197), but with weighted values that emphasize rare but potentially more informative words.

5.3.3 GloVe Embeddings. To capture semantic relationships between words, we employed GloVe (Global Vectors for Word Representation) embeddings.

- **Implementation**: We loaded pre-trained GloVe embeddings (*glove-twitter-100*) and computed the mean embedding for each statement by averaging the embeddings of the words present.
- **Outcome**: This approach yielded a dense matrix with a shape of (12,791, 100), where each statement is represented by a 100-dimensional vector capturing semantic nuances.

5.4 Feature Selection

Given the high dimensionality of our feature sets, particularly for BoW and TF-IDF, feature selection was crucial to enhance model performance and reduce computational complexity.

5.4.1 Chi-Squared Test for Feature Importance. We employed the Chi-Squared statistical test to select the top 100 features most relevant to our target variable (the binary label indicating true or false statements).

- **BoW Features**: The selected features included terms such as *american*, *obama*, *health*, *tax*, and *year*. These words are likely significant in differentiating between true and false statements due to their prevalence in political discourse.
- **TF-IDF Features**: Similar to BoW, TF-IDF highlighted words like *clinton*, *obamacare*, *economy*, and *spending*. The TF-IDF weighting further refined the feature set by emphasizing terms unique to specific statements.

The selection of these features suggests that discussions around prominent political figures and key policy topics are pivotal in classifying statements as true or false.

6 METHODOLOGY

We conduct experiments using various machine learning algorithms and feature extraction techniques to identify the most effective approach for fake news detection.

6.1 Algorithms

- **Naive Bayes (MultinomialNB)**: Suitable for text classification with discrete features, leveraging the assumption of feature independence.

- **Logistic Regression**: A linear model effective for binary classification tasks.
- **Support Vector Machines (SVM)**: Particularly the linear SVM, which performs well in high-dimensional spaces.
- **Random Forest**: An ensemble method that builds multiple decision trees and merges them to improve prediction accuracy and robustness.

6.2 Feature Representations

- **Binary Weighting**: Represents the presence or absence of words in the statements.
- **Count Vectorization**: Statements are represented through the frequency of each word.
- **Term Frequency-Inverse Document Frequency (TF-IDF)**: Weighs words based on their importance, emphasizing those that carry more information by considering their frequency across all documents.

6.3 Preprocessing Steps

- **Text Preprocessing**: Conversion of all text to lowercase, removal of punctuation, special characters, and stopwords to reduce noise.
- **Tokenization**: Breaking down statements into constituent words or tokens for analysis.

7 EXPERIMENTAL SETUP

7.1 Data Preparation

The dataset is split into training and testing sets, ensuring a balanced distribution of true and false statements. Preprocessing steps are applied to clean the data and prepare it for feature extraction.

7.2 Training and Evaluation

Each algorithm is trained using different feature representations. We perform hyperparameter tuning using cross-validation to optimize model performance.

7.3 Metrics

The primary evaluation metric is the **F1-score**, which balances precision and recall:

- **Precision**: The accuracy of positive predictions (i.e., the proportion of statements classified as fake that are actually fake).
- **Recall**: The ability of the model to find all relevant instances (i.e., the proportion of actual fake statements that were correctly identified).

Using the F1-score is crucial because both false positives (misclassifying real news as fake) and false negatives (failing to identify fake news) have significant consequences. We also utilize the confusion matrix to analyze the types of errors made and to fine-tune our models accordingly.

8 CLASSIFICATION MODELS

In our efforts to detect fake news on social media, we implemented several classification algorithms using different feature representations. We focused on models known for their effectiveness in text classification tasks and reduced the number of models to streamline our analysis. Given the critical importance of recall in fake news detection—where missing a fake news instance can have significant consequences—we prioritized models that maximize recall.

8.1 Naive Bayes Classifier

Naive Bayes is a probabilistic classifier based on Bayes' theorem, particularly suitable for high-dimensional data like text due to its assumption of feature independence.

8.1.1 Implementation. We employed the Multinomial Naive Bayes variant, which is effective for text data where features represent term frequencies. The model was trained using three different feature sets: Bag of Words (BoW), TF-IDF, and GloVe embeddings. Cross-validation was performed using 5 folds to assess the model's generalizability.

Table 5: Naive Bayes Recall Metrics

Features	CV Recall	Test Recall
BoW	74.69%	73.23%
TF-IDF	**93.45%**	**92.36%**
GloVe	61.85%	62.09%

8.1.2 Performance Summary. The Naive Bayes classifier achieved the highest recall with TF-IDF features, indicating its effectiveness in identifying fake news instances. The high recall of **92.36%** on the test set demonstrates the model's ability to detect most fake news articles, which is crucial in this application.

8.2 Support Vector Machine (SVM)

Support Vector Machines are powerful classifiers that aim to find the optimal hyperplane separating classes. They are effective in high-dimensional spaces and are known for their robustness.

8.2.1 Implementation. We used a linear SVM with the `LinearSVC` implementation for efficiency. The model was trained on BoW, TF-IDF, and GloVe features, with 5-fold cross-validation to evaluate performance.

Table 6: SVM Recall Metrics

Features	CV Recall	Test Recall
BoW	82.68%	83.11%
TF-IDF	**84.21%**	**84.23%**
GloVe	79.27%	78.56%

8.2.2 Performance Summary. The SVM achieved the best recall with TF-IDF features, attaining a test recall of **84.23%**. This indicates a strong ability to detect fake news, though slightly lower than Naive Bayes with TF-IDF.

8.3 Random Forest Classifier

Random Forests are ensemble models that aggregate the outputs of multiple decision trees to improve predictive accuracy and control overfitting.

8.3.1 Implementation. We trained a Random Forest classifier with 100 trees, using entropy as the criterion for information gain. Cross-validation with 5 folds was performed on each feature set.

Table 7: Random Forest Recall Metrics

Features	CV Recall	Test Recall
BoW	**77.41%**	**77.51%**
TF-IDF	71.70%	70.71%
GloVe	72.64%	72.60%

8.3.2 Performance Summary. The Random Forest achieved its highest recall with BoW features, but overall, its recall was lower than that of Naive Bayes and SVM. The test recall of **77.51%** indicates a moderate ability to detect fake news.

9 MODEL EVALUATION

9.1 Aggregated Performance Summary

We aggregated the performance metrics for all models and feature sets to compare their effectiveness comprehensively. The focus remains on recall, but we present all key metrics for a holistic view.

9.2 Visualization of Results

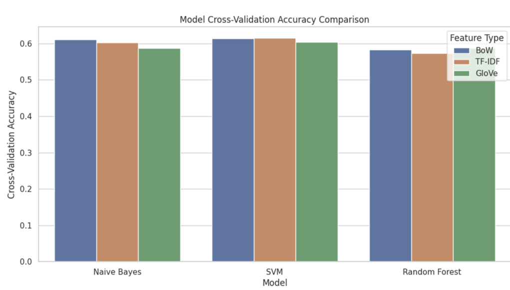


Figure 4: Model Cross-Validation Accuracy Comparison

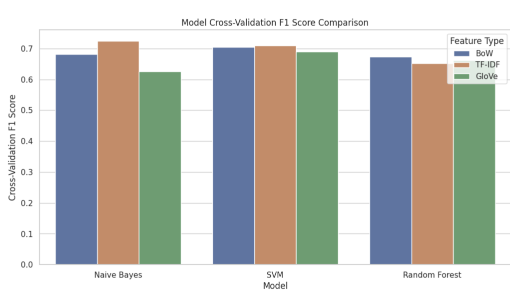


Figure 5: Model Cross-Validation F1 Comparison

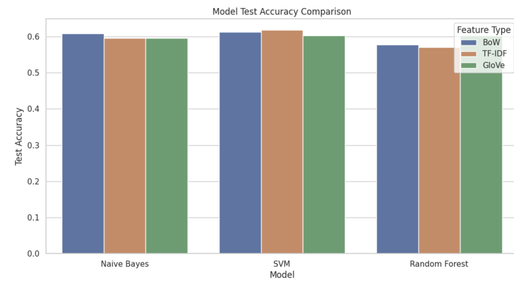


Figure 6: Model Test Accuracy Comparison

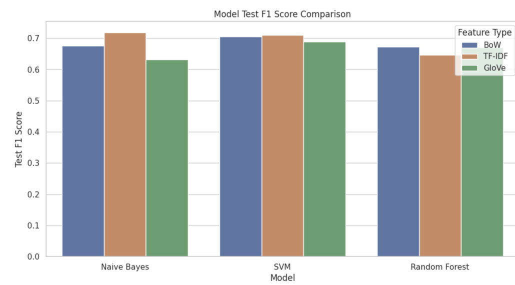


Figure 7: Model Test F1 Comparison

10 ETHICAL CONSIDERATIONS

Detecting fake news involves ethical considerations, particularly concerning censorship and freedom of speech. Our model aims to assist in identifying misinformation without infringing on individuals' rights to express opinions. We acknowledge the potential biases in data and strive to minimize them through careful preprocessing and validation. The goal is to support fact-checking efforts and promote informed decision-making in society.

11 CONCLUSION

In this study, we developed and evaluated machine learning models to detect fake news on social media platforms using textual content. Recognizing the significant impact of fake news on society, our goal was to create an effective tool for classifying news statements as real or fake.

We utilized the PolitiFact dataset, simplifying its original multi-class labels into binary classes to facilitate the classification task. Extensive data preprocessing was conducted, including text cleaning, normalization, and feature extraction. We explored various textual feature representations, namely Bag of Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), and GloVe embeddings.

Our feature engineering process included an assessment of multicollinearity among metadata features using the Variance Inflation Factor (VIF). Due to high multicollinearity, we opted to exclude these features from the final models, focusing instead on the most statistically significant textual features identified through the Chi-Square test.

We implemented three classification algorithms: Naive Bayes, Support Vector Machine (SVM), and Random Forest. The models

Table 8: Aggregated Performance Metrics for All Models

Model	Features	CV Acc.	CV Prec.	CV Rec.	CV F1	Test Acc.	Test Prec.	Test Rec.	Test F1
Naive Bayes	BoW	61.08%	62.70%	74.69%	68.13%	60.87%	62.80%	73.23%	67.62%
Naive Bayes	TF-IDF	60.27%	59.10%	**93.45%**	72.40%	59.50%	58.71%	**92.36%**	71.79%
Naive Bayes	GloVe	58.71%	63.27%	61.85%	62.55%	59.54%	64.20%	62.09%	63.13%
SVM	BoW	61.39%	61.43%	82.68%	70.48%	61.22%	61.23%	83.11%	70.51%
SVM	TF-IDF	61.47%	61.24%	84.21%	70.91%	61.77%	61.48%	84.23%	71.08%
SVM	GloVe	60.37%	61.16%	79.27%	69.05%	60.32%	61.26%	78.56%	68.84%
Random Forest	BoW	58.24%	59.69%	77.41%	67.40%	57.78%	59.30%	77.51%	67.19%
Random Forest	TF-IDF	57.26%	59.73%	71.70%	65.16%	56.99%	59.67%	70.71%	64.72%
Random Forest	GloVe	58.73%	60.89%	72.64%	66.24%	60.20%	62.30%	72.60%	67.06%

were evaluated primarily on recall, given the critical importance of correctly identifying fake news instances. Our results demonstrated that:

- The Naive Bayes classifier with TF-IDF features achieved the highest recall, correctly identifying over 92% of fake news instances in the test set.
- The SVM classifier also performed well with TF-IDF features, achieving a recall of over 84%, while offering a better balance between precision and recall compared to Naive Bayes.
- Random Forest classifiers showed moderate performance, with lower recall rates across all feature sets.

These findings highlight the effectiveness of probabilistic and linear classifiers in fake news detection when combined with appropriate textual feature representations. The high recall achieved by Naive Bayes with TF-IDF features suggests that term weighting schemes capturing word importance are crucial in distinguishing between real and fake news.

Our study contributes to the ongoing efforts in combating the spread of misinformation by providing insights into the most effective machine learning approaches for fake news detection. By focusing on recall, we emphasize the importance of minimizing false negatives in critical applications where undetected fake news can have significant societal impacts.

12 FUTURE WORK

While our models achieved promising results, there are several avenues for future research to enhance fake news detection further.

- **Incorporating Deep Learning Models**: Exploring advanced neural network architectures such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformers (e.g., BERT, GPT) could capture more complex linguistic patterns and contextual information within the text.
- **Utilizing Additional Metadata**: Reintegrating metadata features like *Speaker Job*, *Speaker Affiliation*, and *Subject* using techniques to mitigate multicollinearity could provide additional predictive power. Feature selection methods or dimensionality reduction techniques like Principal Component Analysis (PCA) may help in effectively utilizing these features.
- **Expanding the Dataset**: Incorporating a larger and more diverse dataset, including data from multiple fact-checking organizations and different languages, could improve the model's generalizability and robustness across various contexts.
- **Sentiment Analysis and Stylometry**: Integrating sentiment analysis and stylistic features could enhance the models' ability to detect subtle cues associated with deceptive language.
- **Real-Time Detection Systems**: Developing real-time fake news detection systems that can process streaming data from social media platforms poses challenges in terms of scalability and computational efficiency, which could be addressed in future work.
- **Addressing Ethical Considerations**: Further exploration into the ethical implications of automated fake news detection, including potential biases and the balance between censorship and freedom of speech, is essential for responsible deployment.

By pursuing these directions, future research can build upon our findings to develop more sophisticated models capable of effectively combating the spread of fake news, ultimately contributing to a more informed and resilient society.

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